

EXHIBIT 5



Comment

Sources and influence of perceptual variance: Comment on Dzhafarov's Regular Minimality Principle

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Received 14 February 2005; received in revised form 1 September 2005

Abstract

Dzhafarov [(2002). Multidimensional Fechnerian scaling: Pairwise comparisons, regular minimality, and nonconstant self-similarity. *Journal of Mathematical Psychology*, 46, 583–608] claims that Regular Minimality (RM) is a fundamental property of “same–different” discrimination probabilities and supports his claim with some empirical evidence. The key feature of RM is that the mapping, h , between two observation areas based on minimum discrimination probability is invertible. Dzhafarov [(2003a). Thurstonian-type representations for “same–different” discriminations: Deterministic decisions and independent images. *Journal of Mathematical Psychology*, 47, 184–204; (2003b). Thurstonian-type representations for “same–different” discriminations: Probabilistic decisions and interdependent images. *Journal of Mathematical Psychology*, 47, 229–243] also demonstrates that well-behaved Thurstonian models of “same–different” judgments are incompatible with RM and Nonconstant Self-Similarity (NCSS). There is extensive empirical support for the latter. Stimulus and neural sources of perceptual noise are discussed and two points are made:

Point 1: Models that require discrimination probabilities for noisy stimuli to possess the property that h is invertible would be too restrictive.

Point 2: In the absence of stimulus noise, violations of RM may be so subtle that their detection would be unlikely.

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Keywords: Thurstonian; Regular minimality; Probabilistic; Same–different

1. Introduction

What is a stimulus? Is a precisely prepared aqueous solution of one molar glucose presented to a subject at a specified temperature a stimulus? Even if a one molar solution is presented, the concentration of glucose in the neighborhood of a taste neuron will not be precisely one molar and the temperature from moment to moment and neuron to neuron will vary. Alternatively, is a single molecule of glucose binding to a single receptor a stimulus? However, a stimulus should produce a signal and we cannot expect a single glucose molecule to change cell polarity sufficiently to induce an action potential leading to a recognized signal centrally. Fig. 1 is an illustration of a

general G-protein signal transduction scheme applicable to β -receptor agonists such as adrenaline and chemosensory stimulants. Molecular models of isoboles (points of subjective equality) for mixtures of sweet tasting substances were used to show that sweet taste in humans is mediated by a transducer, such as a G-protein (Ennis, 1991, 2002). For a single substance, the model involves a pair of reversible reactions $A + R \leftrightarrow AR$ and $AR + T \leftrightarrow ART$ where A, the agonist, binds to a receptor R to produce AR and AR binds to T, the transducer, to produce the complex, ART. The percept (sweetness, for example) is assumed to be monotonically related to the concentration of ART and depends on the equilibrium constants for the first and second reactions (affinity and efficacy, respectively.) Variation in the process of inducing a signal may arise in the concentration of the agonist (substance) A, in the environment surrounding the cell (peri-receptor

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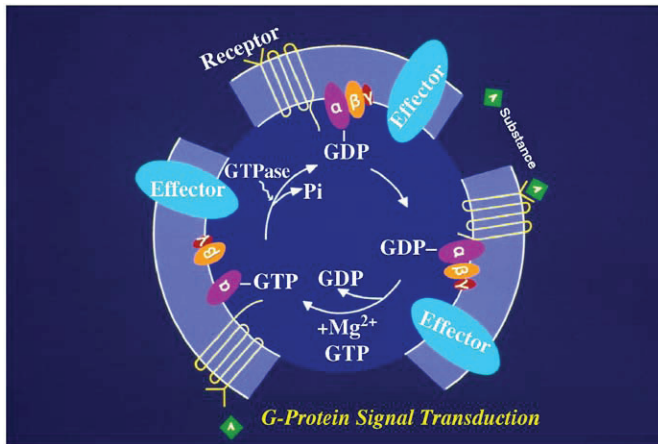


Fig. 1. G-protein signal transduction in which an agonist (A) binds to a transmembrane receptor leading to an exchange of GTP (guanosine triphosphate) for GDP (guanosine diphosphate) and subsequent activation of an effector such as adenylyl cyclase. The receptor may be 7-transmembrane, rather than 5-, as occurs in the chemical senses.

events), or from within and among activated neurons. The first two sources of variation will be called *stimulus noise* and the third source *neural noise*. Both of these types of noise contribute to perceptual variance as discussed in this comment.

Perceptual variation and its effects on observed behavior have been of interest since the earliest attempts to model decision-making. Ennis and Mullen (1992) discussed models that separately account for stimulus and neural noise. In this paper, classical psychophysical functions were combined with Thurstonian ideas about categorical decision-making and perceptual variation. Using the 2-alternative forced choice task (which stimulus is greater or less) it was shown how stimulus variability affects choice outcomes so that different types of hypothesized psychophysical functions could be distinguished. In this paper, a *noisy stimulus* is defined as an object that exhibits stimulus noise and therefore some level of variation will exist due to stimulus presentation or due to peri-receptor events such as, for instance, changes in the composition of saliva or the activity of enzymes that act on an odorant or tastant before it reaches the neuron.

A pair of interesting papers by Dzhafarov (2003a, b) suggest the need for a continued evaluation of the sources and influences of perceptual variance. In these papers, Dzhafarov concludes that commonly used Thurstonian models of same-different judgments are incompatible with two properties that he regards as fundamental to discrimination probabilities. These properties are Regular Minimality (RM) and Nonconstant Self-Similarity (NCSS). Dzhafarov describes stimuli deterministically or precise-valued. This means that, for instance, the same concentration of glucose is presented to neurons in an identical environment from trial to trial. From the previous discussion of sources of noise and Dzhafarov's concept of a

precise-valued stimulus, I assume that the source of noise that he considers is neural.

Dzhafarov describes two observation areas separated spatially or temporally; stimuli are mapped from one area to the other on the basis of minimum discrimination probability and he refers to this mapping as h . A stimulus in one area may not be mapped to the putatively identical stimulus in the other area (due to a constant error) or it might be, in which case h is the identity. The key fact for RM is that h is invertible. RM may be expressed in canonical form (h is the identity) or noncanonical form (h is not the identity). In either form a given row minimum in a matrix of discrimination probabilities for same-different judgments is also the minimum of the column in which it occurs. NCSS occurs when pairs of most similar stimuli (whether putatively the same stimulus or not) differ in their discrimination probabilities.

It is not my intent to challenge or criticize Dzhafarov's conclusions about the incompatibility of RM and NCSS for Thurstonian models. Rather, I would like to challenge his requirement that RM is a fundamental property of discrimination probabilities. I will make two points:

Point 1: Models that require discrimination probabilities for noisy stimuli to possess the property that h is invertible would be too restrictive.

Point 2: In the absence of stimulus noise, violations of RM may be so subtle that their detection would be unlikely.

2. Types of same-different models

Models may be classified according to whether the information or the decision rule are deterministic or probabilistic. Table 1 presents such a classification scheme for "same-different" models. In this table, three types of models for the "same-different" task are presented. Table 1 contains models of Type I (probabilistic information, deterministic decision rules), Type II (deterministic information, probabilistic decision rules) and Type III (probabilistic information, probabilistic decision rules) for the same-different task. All models that assume a probabilistic representation for the information are regarded as Thurstonian (Types I and III). Type I models were published in Ennis and Ashby (1993), Type II in Shepard (1987), Type III in Ennis, Palen, and Mullen (1988) and the connection between Type III models and moment generating functions was described in Ennis and Johnson (1993). Notice that the source of information noise is not specified in this table, it may arise as a result of stimulus events, neural events or both.

The importance of extending Type II models by incorporating perceptual variance to create Type III models became apparent when exceptions arose to Shepard's (1987) proposal that the city-block metric and the exponential decay generalization gradient are universally applicable in models of similarity judgments for sentient

Table 1

Classification of “same–different” models by type of information and decision rule

		Decision Rule	
		Deterministic (D)	Probabilistic (P)
Information	D		<p>Type II</p> $\psi(x, y) = 1 - \exp(-d^\alpha)$ $d = \left\{ \sum z_i ^\gamma \right\}^{1/\gamma}$ <p>Euclidean-Gaussian: $\alpha = 2, \gamma = 2$</p> <p>City-block-exponential decay: $\alpha = 1, \gamma = 1$</p>
	P	<p>Type I</p> $\psi(x, y) = 1 - \frac{1}{(2\pi)^{n/2}} \int \frac{\exp[-0.5(\mathbf{z} - \boldsymbol{\mu})' \mathbf{V}^{-1}(\mathbf{z} - \boldsymbol{\mu})]}{ \mathbf{V} ^{1/2}} \left\{ \begin{array}{l} 1, \mathbf{z}' \mathbf{z} < \tau^2 \\ 0, \mathbf{z}' \mathbf{z} \geq \tau^2 \end{array} \right\} d\mathbf{z}$ $= 1 - \sum_{j=0}^{\infty} e_j \Pr \left(\chi_{n+2j}^2 < \frac{\tau^2}{\beta} \right)$	<p>Type III</p> <p>Euclidean-Gaussian case</p> $\psi(x, y) = 1 - (\ \mathbf{V}\ \mathbf{J})^{-1/2} \exp[\boldsymbol{\mu}'(2\mathbf{J}^{-1} - \mathbf{I})\boldsymbol{\mu}]$ $\mathbf{J} = \mathbf{V}^{-1} + 2\mathbf{I}$ <p>In one dimension</p> $\psi(x, y) = 1 - \exp \left[\frac{-\boldsymbol{\mu}^2}{1 + 2(\sigma_x^2 + \sigma_y^2)} \right] \sqrt{1 + 2(\sigma_x^2 + \sigma_y^2)}$

Type II models are due to Shepard (1987) and the other models are referenced in the text.

\mathbf{z} is the difference between momentary perceptual magnitudes; $\boldsymbol{\mu}$ and \mathbf{V} are the mean and variance–covariance matrix of perceptual differences, respectively; σ_i^2 is the variance of z_i for the i th dimension; τ is a decision criterion and β is an arbitrary constant that affects the rate of series convergence; e_j depends on $\boldsymbol{\mu}$ and \mathbf{V} Ennis and Ashby (1993).

organisms. If stimuli are separable and confusable it was shown that a Type II modeler may find support for the Euclidean metric and a Gaussian generalization gradient when the underlying structure may involve, as Shepard proposed, the city-block metric and an exponential decay gradient (Ennis, 1988a, b; Nosofsky, 1988; Shepard, 1988). Intuitively, Gaussian noise appeared as a Gaussian generalization gradient in the absence of a parameter to account for it. The inclusion of perceptual noise in models of same–different judgments was useful to enrich our understanding of perceptual representations; in the present case it may prove useful to further enrich that understanding by considering the components of perceptual noise.

3. Point 1. Models that require discrimination probabilities for noisy stimuli to possess the property that h is invertible would be too restrictive

Consider the following example, taken from Ennis and Mullen (1992). Using upper case for random variables and lower case for their realizations, S_i is a stimulus random variable and

$$\log S_i \sim N(\mu_i, \sigma_{S_i}^2),$$

where μ_i is the mean of the logs of the stimulus magnitudes and $\sigma_{S_i}^2$ is their variance. N_i is a neural random variable and

$$n_i = c \log S_i,$$

where c is a constant. Z_i is a psychological magnitude and $Z_i \sim N(c\mu_i, c^2\sigma_{S_i}^2 + \sigma_{N_i}^2)$,

where $\sigma_{N_i}^2$ is the neural variance. (Each value of n_i is the mean of a normal distribution with this variance.)

From the Type III same–different model in Table 1,

$$\psi(x, y) = 1 - \frac{\exp\left[\frac{-c^2(\mu_x - \mu_y)^2}{1 + 2[2\sigma_N^2 + c^2(\sigma_{S_x}^2 + \sigma_{S_y}^2)]}\right]}{\sqrt{1 + 2[2\sigma_N^2 + c^2(\sigma_{S_x}^2 + \sigma_{S_y}^2)]}},$$

where σ_N^2 is the common neural variance for different stimuli. If $\mu_x = \mu_y$ and $\sigma_{S_x}^2 > \sigma_{S_y}^2$, the mapping, h , will not be invertible because $\psi(x, x) > \psi(x, y) > \psi(y, y)$. Consequently, the minimum of a row of discrimination probabilities will not be the minimum of the column in which it occurs. This example involves fairly reasonable assumptions: stimulus magnitudes are log-normally distributed, a logarithmic psychophysical transformation occurs and neural noise follows a normal distribution. It is quite easy to demonstrate experimentally with, for instance, line lengths drawn from distributions with equal means and different variances that h will not be invertible. Since it is a common objective in applications involving consumer products or brand images to reduce stimulus variance without changing the mean, the imposition of invertibility on h would be too restrictive in modeling same–different discrimination probabilities. One could construct other examples involving stimulus noise which occur in practice in which means are not identical and h would not be invertible. Dzhaferov's analysis of well-behaved Thurstonian same–different models for precise-valued stimuli shows that under certain conditions these models will

predict that h is not invertible. Since Dzhaferov (2003a, b) defines RM with respect to precise-valued stimuli, the lack of invertibility of h for noisy stimuli is not relevant to his discussion of RM. However, since all stimuli exhibit some degree of physicochemical noise, he exempts practical applications of Thurstonian models by requiring that stimuli are precise-valued.

4. Point 2. In the absence of stimulus noise, violations of RM may be so subtle that their detection would be unlikely

Dzhaferov's requirement that RM is a fundamental property of discrimination probabilities is based on experiments in which stimulus noise is at most a minor component of variation and theoretically he treats stimuli deterministically or precise-valued. This implies that the variance in Dzhaferov's experiments is primarily neural in origin. It would seem to be impossible for an experimenter to identify a precise-valued stimulus in the chemical senses or in consumer product testing. However, imagine that such a stimulus exists or that neural variance is much larger than stimulus variance. If it could be established that RM and NCSS are fundamental properties of discrimination probabilities one would have to ask why extra-cellular (stimulus) sources of variance would differ in their effect from neural sources. It would certainly call into question the concept of neural variance as it is used in Thurstonian models of same–different judgments.

When variance is primarily neural in origin, stimuli with identical means probably have identical variances (they are the same stimulus) and so the particular result discussed earlier demonstrating that h is not invertible with noisy stimuli may not arise in practice. For example, a Type III

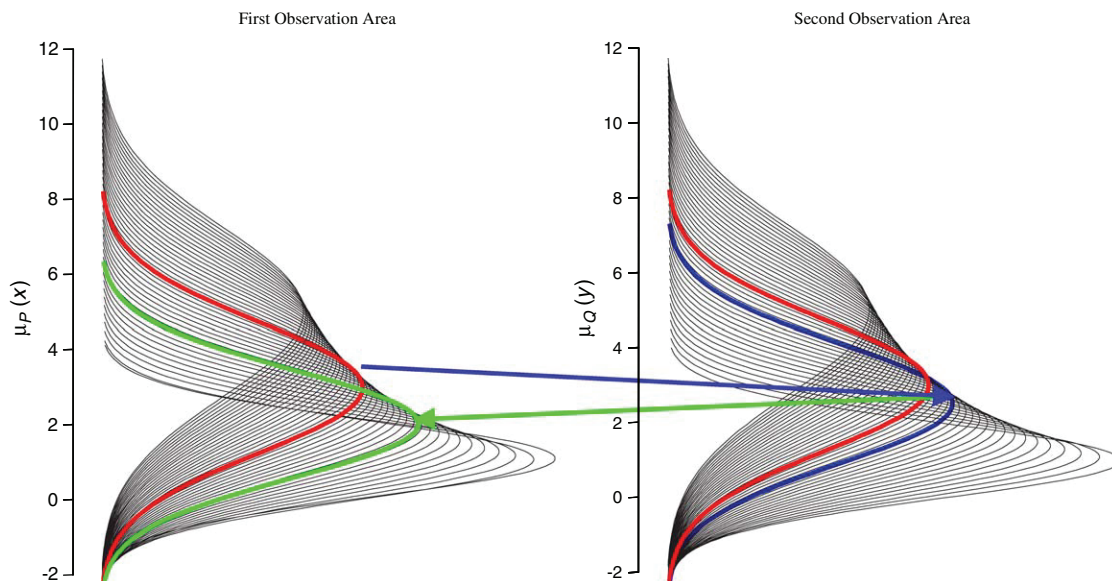


Fig. 2. Mapping between two observation areas with stimuli represented as normal distributions with means from 1.0 to 5.0 and variances equal to the means. The mapping, h , based on minimum discrimination probability (Type III model) takes the stimulus with mean 3 in the first observation area to a stimulus with lower mean in the second area as indicated by the arrow. The mapping is not invertible as shown by the second arrow.

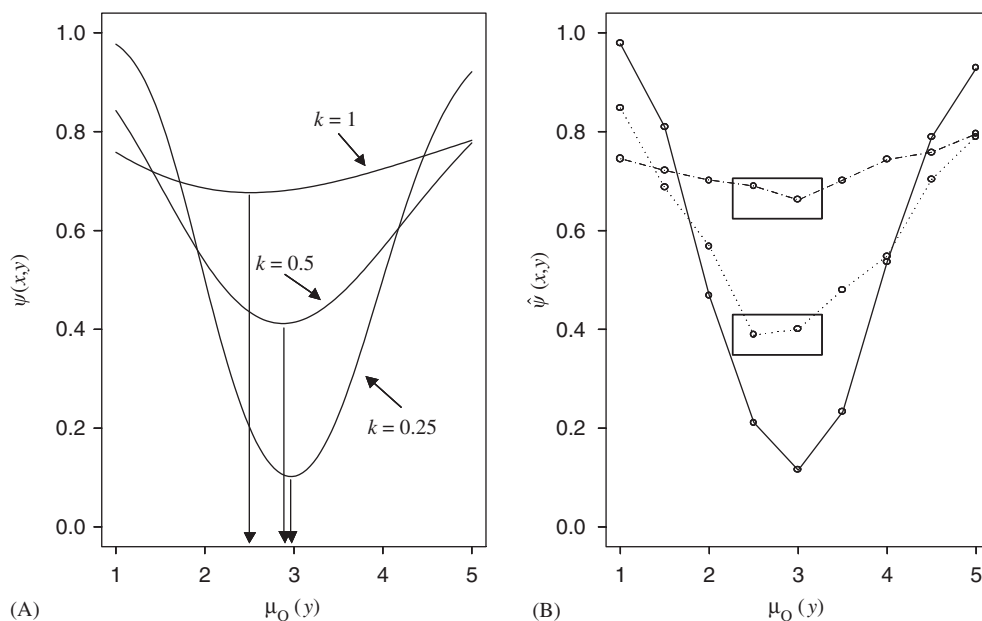


Fig. 3. Discrimination probabilities for pairs of objects in which the stimulus in the first observation area is mapped to random images with mean 3 and standard deviation $k\sqrt{3}$ and stimuli in the second observation area are mapped to random images with mean $\mu_Q(y)$ and standard deviation $k[\mu_Q(y)]^{1/2}$. (A) Theoretical values for the discrimination probabilities with arrows indicating minima (violations of regular minimality). (B) Experimental estimates of discrimination probabilities based on 600 randomly selected values. A 95% confidence region is indicated by the height of the rectangles.

Thurstonian account of the Rothkopf Morse code data (Ennis et al., 1988) showed that no two signals had identical means; they had different variances that explained the nonconstancy of the diagonal of the same–different matrix and the higher variances were associated with the most densely populated regions of the perceptual space. A possible exception to the idea that stimuli with equal perceptual means have equal perceptual variances is when two stimuli (such as fructose and glucose) produce the same effect (sweetness) by different transduction mechanisms (Ennis, 1991, 2002.) In this case, when the stimuli are particular concentrations of the substances that produce equal effect, their perceptual variances may not be identical. In addition, of course, there would be stimulus variance in this case. Another exception might occur when subjects are presented with precise-valued stimuli under different drug interventions that might alter perceptual variance but not means.

As an illustration in discussing Thurstonian models, Dzhamfarov (2003a) considered that perceptual variances are a positive multiple (k^2) of the means of random images representing stimuli. For two stimuli this choice of variance leads to equal variance when means are equal. Fig. 2 illustrates two observation areas in which normal distributions corresponding to the perceptual values of precise-valued stimuli are drawn. Means of the distributions in each area fall between 1 and 5 and their variances are equal to their means ($k = 1$). As predicted by Dzhamfarov (2003a) a Type III Thurstonian model will not produce an invertible mapping between the two observation areas based on minimum discrimination probability as shown in

Fig. 2. Fig. 3A shows the theoretical discrimination probability from a Type I Thurstonian model for pairs of stimuli (3,1:5) with $k = 0.25, 0.5$ and 1 and the criterion for declaring “same”, $\tau = 1$. In this case there is no constant error. (Representations of the stimuli in the two observation areas are identical. In addition, the mapping is not invertible so constant error is not a well defined concept.) RM would hold if the minimum discrimination probability corresponds to a mean of 3. From Fig. 3A, departure from 3 at the minimum discrimination probability increases as k increases, but differences in discrimination probability become quite small. In fact, Fig. 3B shows that if 9 stimuli are chosen around the mean of 3 and 600 judgments per mean are obtained (similar to Dzhamfarov’s experiments), it would not be possible to rule out a violation of RM. This is evident from both the location of the minima in the simulation and the 95% confidence interval for the discrimination probabilities. Figs. 4A and B show a similar result and also demonstrate that discrimination probabilities for most similar stimuli may differ for different stimuli (note the relative heights of the curves in Fig. 3A versus 4A) as required for NCSS.

A similar result to that shown in Figs. 3 and 4 can be demonstrated for a Type III Thurstonian model. As shown in Table 1, the discrimination probability for the multivariate Euclidean–Gaussian case is

$$\psi(x,y) = 1 - (|V||J|)^{-1/2} \exp[\mu'(2J^{-1} - I)\mu], \quad (1)$$

where μ and V are the mean vector and variance–covariance matrix of perceptual differences, respectively, and

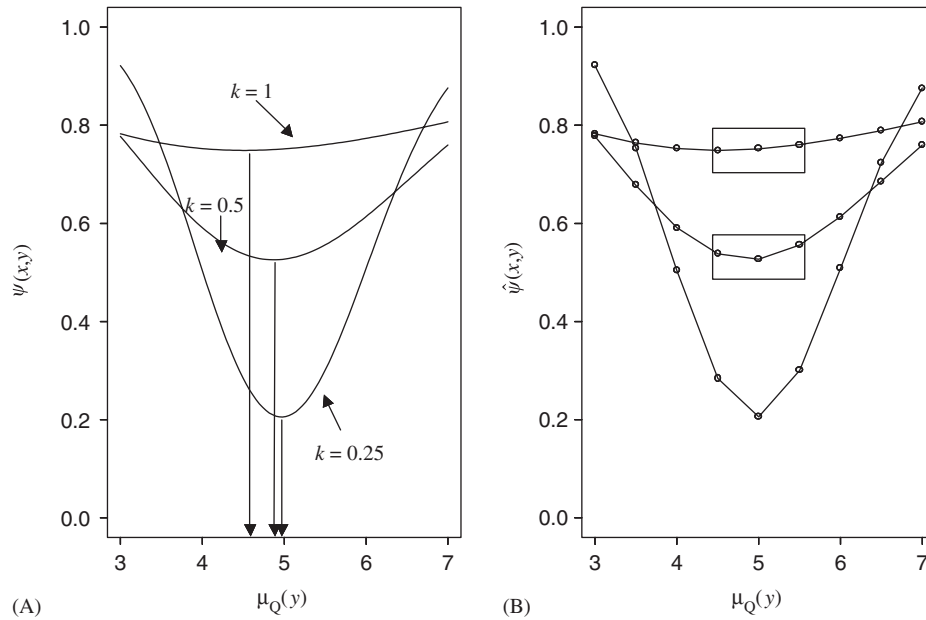


Fig. 4. Discrimination probabilities for pairs of objects in which the stimulus in the first observation area is mapped to random images with mean 5 and standard deviation $k\sqrt{5}$ and stimuli in the second observation area are mapped to random images with mean $\mu_Q(y)$ and standard deviation $k[\mu_Q(y)]^{1/2}$. (A) Theoretical values for the discrimination probabilities with arrows indicating minima (violations of regular minimality). (B) Experimental estimates of discrimination probabilities based on 600 randomly selected values. A 95% confidence region is indicated by the height of the rectangles. The values of the minimum discrimination probabilities are higher than in Fig. 3A.

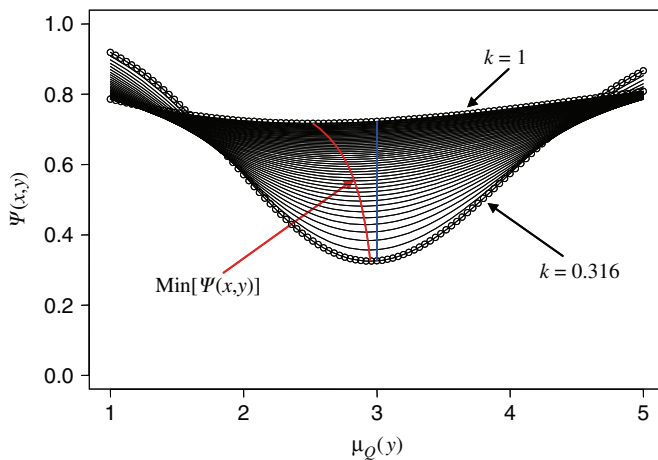


Fig. 5. The relationship between discrimination probabilities for a Type III Thurstonian model and the perceptual mean in the second observation area with the mean in the first area set to 3. Minimum discrimination probabilities are shown when k is between 0.316 and 1 (lower to higher curves) along with the discrimination probabilities at a mean of 3 in the second observation area.

$J = V^{-1} + 2I$. In one dimension,

$$\psi(x, y) = 1 - \frac{\exp(-\mu^2/a)}{\sqrt{a}}, \quad (2)$$

where $\mu = \mu_P(x) - \mu_Q(y)$, $a = 1 + 2(\sigma_x^2 + \sigma_y^2)$, $\sigma_x^2 = k^2\mu_P(x)$, and $\sigma_y^2 = k^2\mu_Q(y)$.

For a fixed perceptual mean in the first observation area, the discrimination probability in this model depends only on the value of k and the perceptual mean in the second

observation area. Fig. 5 shows the discrimination probability for various values of k and $\mu_Q(y)$ when $\mu_P(x) = 3$. The figure also shows the location of the minimum points on each curve from the root of $d[\psi(x, y)]/d[\mu_Q(y)] = 0$. Adjacent to this line showing the most severe violations of RM from the model is the line corresponding to the discrimination probability expected if discrimination probabilities had the RM property (there is no constant error, so the stimulus in the first observation area should be identical to the stimulus in the second observation area and generate the same perceptual mean.) It can be seen that when $k = 0.316$, the difference between the two discrimination probabilities is negligible, as was shown for the Type I model. As k increases to 1, departures from RM expressed in terms of $\mu_Q(y)$ increases, but the differences between the discrimination probabilities remains very small. Fig. 6 shows the 95% confidence region for discrimination probabilities for $\mu_P(x) = \mu_Q(y) = 3$ with $k = 0.316$ and $k = 1$. It is clear from these examples that experiments of impractical size (exceeding 100,000 judgments if $k = 0.316$) would be needed to establish that a RM violation has occurred.

RM is usually diagnosed in matrices of discrimination probabilities by inspecting the matrices (Dzhafarov, 2005, personal communication). If two pairs of stimuli are chosen from the two observation areas, $\mu_P(x) = \mu_Q(y) = 2$ and $\mu_P(x) = \mu_Q(y) = 4$, the discrimination probabilities for each pair for a Type III model with $k = 0.316$ and 600 judgments will be significantly different 98% of the time at an α of 0.01. If we then construct stimuli so that the means in the first observation area are 2, 2.5, 3, 3.5 and 4 and we

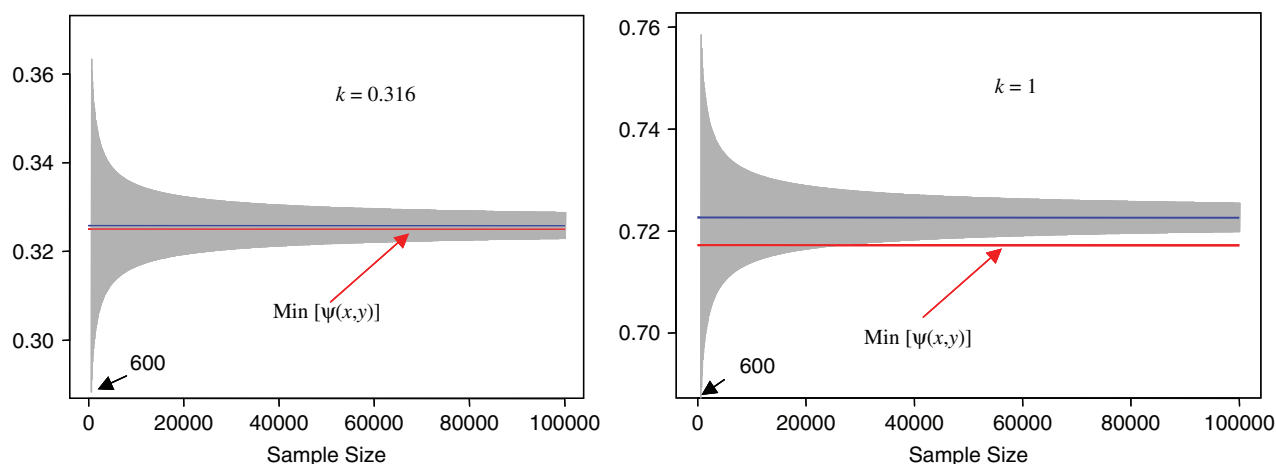


Fig. 6. 95% confidence regions for discrimination probabilities based on a Type III model with $\mu_p(x) = \mu_Q(y) = 3$ with $k = 0.316$ and $k = 1$. The minimum discrimination probability for this stimulus is also shown.

construct an identical set in the second area, how often would we observe a RM violation based on a Type III Thurstonian model with $k = 0.316$ and 600 judgments per discrimination probability? A simulation involving 1000 such experiments and inspection of their matrices shows that violations of RM will occur very rarely. 99.3% of the time RM (in canonical form) was supported on inspecting the matrices. In the very few cases (0.7%) where it was not, evidence for the violation was extremely subtle. Although Dzhafarov correctly concludes that a well-behaved Thurstonian model of same–different judgments will exhibit an incompatibility between NCSS and RM, his apparent support for RM is highly predictable from the same Thurstonian model that violates RM under the assumptions about neural variances made in this section. The conditions required to see NCSS are incompatible with those required to detect a violation of RM in the cases discussed.

5. Conclusions

Dzhafarov (2003b) suggests a reexamination of the Thurstonian framework for interpreting “same–different” judgments because well-behaved Thurstonian models are incompatible with two properties of discrimination probabilities that he regards as fundamental, RM and NCSS. Since Dzhafarov describes stimuli as precise-valued, his conclusion regarding the incompatibility of RM and NCSS does not apply to noisy stimuli as described in this comment and it is easy to show that the mapping between observation areas may not be invertible when stimuli possess stimulus noise. The imposition of invertibility of this mapping on models of discrimination probabilities would be highly restrictive, particularly when stimulus variance is a primary source of perceptual variance as occurs in practical applications of Thurstonian models. In the hypothetical case where there is no stimulus noise or in experiments where neural noise is the primary source of

perceptual variance, violations of RM may be subtle and difficult to detect experimentally, often not exhibited in matrices of same–different discrimination probabilities. Under the assumptions made it seems that the conditions leading to more confidence in observing NCSS are those that increase the likelihood of observing RM in an experiment. Thurstonian probabilistic models use very simple and intuitive representations of stimuli from which linkages among different methods of measuring human behavior can be achieved efficiently through a common set of parameters. The extensibility of these models to build a comprehensive structure for decision-making has many applications in a broad range of behavioral disciplines.

Acknowledgments

The author is deeply indebted to Ehtibar Dzhafarov for his generosity and encouragement and to Philip Smith, the action editor, for a very formative discussion during the preparation of this comment. Two anonymous reviewers provided helpful suggestions and criticism.

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